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IS SOUND JUST NOISE?

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Abstract

This paper analyzes the information content of the ambient noise level in the Chicago Board of Trade's 30-year Treasury Bond futures trading pit. Controlling for a variety of other variables, including lagged price changes, trading volumes, and news announcements, we find that the sound level conveys information which is highly economically and statistically significant. In particular, we find increases in the sound level precede periods of high price volatility and increased trading volumes. Increases in the sound level also presage the placement of block trades and relative increases in customer-driven trading. Our results add to our understanding of the market price formation process and offer important implications for the future of open outcry and floor-based trading mechanisms.

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1 Introduction

The scope of information processed by traders in arriving at supply and demand schedules represents an important dimension to the equilibrium price formation process. Authors in the market microstructure literature, most notably Glosten and Milgrom (1985) and Kyle (1985), offer important insights. By considering settings where traders incorporate information contained in prices into their decision rules, they enhance our understanding of how markets arrive at equilibrium prices. However, investigation of the role of other public signals in influencing the behavior of market participants has been fairly limited.[1] The implicit assumption is that past prices, trading volumes, news announcements, and perhaps the composition of a limit order book reflect all public information useful to a trader at a given point in time.

However, in most markets the exchange of additional information is critical. Participants are constantly obtaining signals to determine the nature of the supply and demand curves against which they trade or compete to trade. For instance, knowing a car dealer's inventory level is useful to the purchaser of a new car. As a signal of the slope of the dealer's supply curve, such information helps identify effective negotiation strategies. Similarly, a homebuyer finds important information in the level of interest of others in attendance at an open house. By determining the nature of competition in the bidding for the home, a buyer improves her chances of posting a winning bid while mitigating the winner's curse.

In this paper, we challenge the notion that past prices, quantities, and news announcements represent the scope of inputs for the market's process of price formation. We seek to determine whether traders in certain financial markets convey to each other information about their eagerness, their future intentions, or their perceptions of market conditions. We ask whether such signals contain useful information for predicting future market conditions, such as volatility, depth, or composition of trade. If so, it is conceivable that markets

[1]Benveniste, Marcus, and Wilhelm (1992) examine the role of professional relationships which evolve on trading floors in setting prices. Bias, Hillion and Spatt (1997) examine the price formation process during the pre-opening period in the Paris Bourse. DeMarzo, Vayanos, and Zweibel (1998) explore some theoretical implications of allowing for communication among traders in asset pricing.

which accommodate such exchange arrive at prices more efficiently than those that do not.

Indeed, existing financial markets vary widely in terms of their ability to accommodate the exchange of information among traders. On the one hand, in the open outcry and floor exchange settings, with their face-to-face interaction among locals, specialists, and floor brokers, such exchange would appear to be commonplace. On the other hand, the ability of the computer networks of newly emerging electronic exchanges in Frankfurt and Paris to accommodate and aggregate trader signals beyond quotes, transactions, or limit orders appears limited. This research, in seeking to identify and understand the role the exchange of non-transaction information, has potentially important implications for the future of open outcry and floor exchange mechanisms. If there exists information that is regularly conveyed among traders in the open outcry and floor exchange settings, which cannot easily be replicated and conveyed across an electronic exchange, then electronic exchanges are not merely low-cost substitutes for the open outcry/floor trading mechanisms.

To identify non-transaction information, we focus on the open-outcry futures market. In an open outcry exchange, traders stand in a large "pit" and bark out the prices and quantities at which they are willing to buy and sell. Until recently, this system was the undisputed mechanism for allowing many individuals to concurrently trade large volumes of a given security.[2] The open outcry market, with its face-to-face trading among many participants at once, maximizes our prospects for identifying conveyance of non-price information. In order to identify whether, and to what extent, non-price information is important, we need a measure that identifies times of high degrees of such communication among traders.

One measure that is likely to capture times of high trader communication is the sound level in the pit – or what's commonly referred to by traders as the "buzz" of the pit. Traders standing in an open outcry pit can easily hear how loudly and how often their competitors shout out their orders, and may glean useful information from this activity. A number of possibilities exist for why the sound level might be informative. First, the

[2]The top-3 futures exchanges, the Chicago Mercantile Exchange, the London International Financial Futures Exchange, and the Chicago Board of Trade all use open-outcry to trade most of their contracts.

sound level might signal useful information regarding the composition of expected volume at a given point in time. Changes in the sound level may indicate larger trade sizes, more broker-generated order flow, or broader trader participation rates. The sound level might also signal information regarding the arrival of private information into the market and the degree to which the current order flow is informed. Finally, the sound level may contain information about the current price elasticity or the current conditional volatility. A high sound level may indicate that little depth exists at or immediately beyond the bid or the ask and that additional trades may move the price substantially in one direction or the other. It is important to note, however, that the signals which are being conveyed and processed are likely to be extremely subtle and complicated. The sound level is at best an extremely crude approximation of the level of this conveying and processing activity.

Some evidence does exist which indicates that traders find ambient noise informative. First, Madhavan and Panchapagesan (1998) point out that New York Stock Exchange (NYSE) specialists often cite the sound level as containing information that is useful for setting prices. Second, when the financial product trading floor of the Chicago Board of Trade (CBOT) was moved to a new building in 1997, traders in the 10-year note pit complained they had less 'feel' for what was happening in the bond pit. Their new pit's location was no longer adjacent to the bond pit, but now separated from it by 25 feet. When the CBOT responded by placing television monitors in the center of the 10-year pit with live video feed from the inside of the bond pit, the monitors went unused. This suggests that traders in the 10-year pit view the sound level of the bond pit to be important information that cannot simply be reconstructed from other publicly observable variables.

We focus on high-frequency measures of the sound level in the CBOT's 30-year Treasury bond futures pit. The bond pit, with over 400 pit participants and the world's second largest volume levels,[3] offers an ideal setting in which to test the importance of sound. Our study finds that after controlling for other observable information, changes in the sound level

[3]The CBOT's bond futures traders traded 99,827,659 contracts in 1997. Only the CME's Eurodollar futures contract exhibited greater volume.

at a given point in time contain information regarding the nature of prices, volumes, and volatilities traders can expect to face in the future. We find that, after conditioning on available transaction information, increases in the sound level precede periods of greater volatility, higher trading volume, increased frequency of block trading, and larger share of customer-based trades. The high statistical and economic significance of the results indicates that non-transaction communication among traders is central to the determination of market equilibrium in an open outcry exchange.

The paper proceeds as follows. Section 2 contains a discussion of the ambient noise level, the circumstances under which sound may contain useful information, and what kinds of information might be expected from the sound level. In Section 3, we outline the features of the sound, price, and trade data used in this study, commenting on a number of data collection and implementation issues. In Section 4, we consider the informativeness of the sound level for predicting the likelihood of future price changes over short horizons. In Section 5, we analyze the importance of the sound level at the minute frequency in accounting for future changes in prices, volume, trade breadth, and trader type. Section 6 discusses some robustness issues and Section 7 concludes the paper.

2 Sound Levels and Open Outcry

In the past decade, improvements in computer technology have given rise to a number of electronic alternatives to the open outcry market. Electronic exchanges in the U.S. and Europe have emerged as threats to open outcry's position as the standard for trading highly liquid securities. In 1990 the Deutsche Terminborse (DTB) began electronic trading of the 10-year German government bond futures contract, offering investors an alternative to the open-outcry setting offered by the London International Financial Futures Exchange (LIFFE). By April 1998, the DTB had captured 81% of the Bund market. Recently, traders in LIFFE's Euromark contract (LIFFE's strongest product) threatened to switch their trades to the DTB, blaming the inefficiencies of the open-outcry mechanism. In the summer of 1998, the French futures exchange, Matif, opened electronic trading alongside its open outcry markets. By the end of the summer, trading in short-term interest rate futures had migrated entirely to the computer terminals.

In the U.S., the CBOT, which has traded futures contracts in an open outcry exchange since 1948, has recently seen its 30-year U.S. Treasury bond futures contract come under threat from electronic competition. In the fall of 1997, Cantor Fitzgerald, the world's largest inter-dealer government bond broker, applied for a license to offer electronic trading of 30-year US Treasury Bond futures contracts. During the subsequent week, CBOT seat prices fell by 30% and were down a total of over 50% a year later. In September 1998, Cantor gained CFTC approval and began placing electronic orders.

Much of this suggests that electronic trading, in spite of its inherent limitation on participant communication, is nonetheless more efficient than open outcry. Indeed, Breedon and Holland (1998), who examine concurrent trading in the LIFFE and DTB Bund markets, find bid-ask spreads were generally lower on the DTB's electronic exchange than LIFFE's open outcry market. Nevertheless, they find that volumes tended to migrate to the open-outcry setting during periods of high volatility, indicating that there were conditions under which participants viewed open outcry as superior.

This study instead focuses on market inputs to identify material differences between open outcry and electronic exchanges. In doing so, we ask whether there exists information which is regularly communicated across an open outcry pit but cannot be easily transmitted over a computer network. We propose a number of hypotheses for why the sound level, in particular, may convey important information about future market conditions. The first possibility is that a higher sound level precedes periods of increased volatility. In an open outcry setting, traders can only see directly the quantity being offered for purchase or sale at the current bid and ask. Although certain electronic exchanges allow participants to see the limit order book, since it generally contains an indication of only a certain fraction of the volume that can be expected at a given future price (and a potentially misleading indication thereof), it may be a poor substitute for the true supply and demand schedules at a given point in time.[4] The sound level may convey more complete information concerning traders' perceptions of the price elasticity at a particular point in time. A perception of weak support beyond the bid or ask may lead traders to be particularly vocal to improve their chances of securing remaining contracts.

In addition, an increased sound level could signal to market participants the perception that private information is arriving into the market. Traders eager to mitigate adverse selection costs or lower exposures may begin activity to unwind their positions. If such efforts manifest themselves in a higher sound level relative to the volume of trade, they are likely to convey information that is of use to others in determining the likelihood of future price changes – particularly changes with a high associated degree of adverse selection. This leads us to Hypothesis 1.

Hypothesis 1 *Conditional on all available transaction information, an increase in the current sound level leads to a higher probability of future price changes.*

A second possibility is that due to past price changes or trading patterns, there may be times when a large number of locals need to balance out their inventories or a number of brokers are holding unfilled discretionary orders. For a while, these traders may try to obtain a favorable price in executing their trades, leading to an increased sound level. If faced with increasing pressure to get the orders filled and inventories rebalanced, there may be a point at which these traders begin to hit the market's bids and asks. As a result, the rise in sound will tend to be followed by an increase in trading activity beyond that accounted for by concurrently observable information. Again, the increased sound level could also signal the coming arrival of private information, and lead to an increase in overall trading activity as traders seek to position themselves to mitigate adverse selection costs. We capture these possibilities in Hypothesis 2.

Hypothesis 2 *Conditional on all available transaction information, an increase in the current sound level leads to an increase in future trading volume.*

[4] McInish and Wood (1995) find latent or "hidden" limit orders to be an important counterpart to the NYSE's displayed limit order book.

Additionally, ambient noise may contain information regarding the *nature* of trading expected to take place in the future. For example, if traders anticipate the entry of a few large trades into the market, they may wish to position themselves differently than if they anticipate more dispersed future trading. In this case, the sound level would rise when traders are more actively attempting to position themselves favorably for the anticipated change in trading breadth. The possibility that sound may indicate the changes in future market breadth is expressed in Hypothesis 3.

Hypothesis 3 *Conditional on all available transaction information, an increase in the current sound level leads to a change in overall market breadth.*

At the extreme, traders may somehow identify a large block trade that is about to enter the market. For example, traders in the T-bond pit have been known to steal signals from brokerage houses and identify an incoming large order before it reaches the market. In cases such as these, the sound level, as a reflection of trader activity to adjust their portfolios or their bid/ask quotes prior to the execution of a large order, may forecast the arrival of a block to the market. Alternatively, prior to the placement of a large trade, a broker may find it optimal to indicate his intentions and to ensure that sufficient depth exists to rapidly absorb the order. This would be similar to the price discovery process which takes place during the pre-opening period of the Paris Bourse, documented by Bias, Hillion, and Spatt (1997). There, prior to the establishment of the opening price, traders find it optimal to gauge market depth by posting informative, non-binding orders and observing the resulting indicative prices. These possibilities for the relationship between sound levels and block trades are expressed in Hypothesis 4.

Hypothesis 4 *Conditional on all available transaction information, an increase in the current sound level leads to a greater likelihood of a block trade arrival.*

Finally, if traders can anticipate the type of trades they will face in the future, they may alter their current trading strategy. This may be particularly important if customer-based trades have different informational characteristics than trades of locals. For instance, if trades placed by brokers are viewed to be more "informed" than those placed by locals, traders may react when anticipating a shift in the composition of order flow. If traders forecast an increase in the amount of broker-placed trades, they may submit bid or ask quotes less aggressively than otherwise or work harder to unwind current positions in order to mitigate any adverse selection. Hypothesis 5 captures this possibility.

Hypothesis 5 *Conditional on all available transaction information, an increase in the current sound level leads to a change in the expected future balance of orders between locals and brokers.*

3 The Data

3.1 Data Collection

To conduct this study, we took second-by-second sound level readings from the CBOT bond pit over a two-month period in 1998 – from May 20th to June 19th and from July 30th to September 2nd.[5] To take sound level readings, we pointed a directional microphone into the pit from the top of the 20-ft price recorders' tower located at the edge of the pit. The sound level was sampled across 128 different frequencies and recorded with a timestamp.

In conjunction with the sound data, we use the CBOT's second-stamped price and trading volume data of the front-month Treasury bond futures contract.[6] The price data is obtained from the CBOT's "time and sales" dataset. Prices are recorded by observers who stand in the price recorder tower (called "Radio"). They watch continuously for signals of executed trades and immediately record whenever a trade occurs at a new price. These updated prices are then posted on the digital readouts in the trading room and broadcast

[5]We were unable to collect data during the intervening period due to problems with the sound recorder – we forgot to disable the laptop's auto-suspend feature.

[6]The front-month contract is the contract 1-4 months to delivery and accounts for over 90% of the volume. Non-front-month contracts may be traded only at the center of the pit.

around the world. The timing of price changes is typically accurate to within one second.[7] During the first half of our sample period, the Bond futures market was relatively calm, with total trading volume of 9,054,113 contracts in May (average monthly volume in 1997 was 8,318,972 contracts), and prices hovering in the $120\frac{9}{32}$ to $124\frac{1}{8}$ range. The second half of our sample was considerably more active. The Bond pit set records for total volume, with 12,024,762 contracts traded during August, and prices ranged from $121\frac{3}{4}$ to $127\frac{1}{2}$.

The trade data is obtained from the CBOT Office of Investigations and Audits (OIA). The trades are determined by matching the time stamps of the buy and sell receipts obtained from trader clearing houses with the time stamps of the time and sales data. For each trade, the identity of the buyer and seller are recorded,[8] as well as a code distinguishing between trades placed by brokers, by locals, on behalf of other traders, or on behalf of clearing firms.

Finally, in addition to the sound, price and volume data, we include in our analysis time and sales data from the Dow futures contract which also trades on the financials floor of the CBOT as well as the timing of any scheduled treasury news announcements. Our complete dataset consists of 1,075,447 seconds during which frequency levels and any trades, changes in Bond or Dow prices, or known news announcements that occurred were recorded.

3.2 Data Cleaning

There are several problems with our data that required attention prior to any analysis. First, we had several difficulties ensuring that the time stamps on each of our datasets were accurate to the second. Since our tests focus on identifying statistical causality, it is extremely important that the time-stamps on our sound level and price and trade data are precisely synchronized. Because our sound recorder's clock drifted by a few seconds each day relative to that of the exchange, this was a non-trivial problem. However, we correct

[7] A small fraction (less than 1%) of the trade prices are incorrectly posted and later revised. Although we use the revised data, our results are robust to dropping these observations.

[8] To protect traders' identities, but still allow us to track their trading activity, trader identities are encrypted.

for this by recovering the opening and closing exchange bells from an analysis of the sound level at particular frequencies, and using these to interpolate time stamps which exactly match those of the exchange's price and trade data. Although we are confident our time stamps are accurate to within one second, we include some tests to verify that our results are robust to any remaining timing inaccuracies.

The CBOT claims the OIA trade data is recorded accurate to the second over 95% of the time. Since the transactions are reconstructed after-the-fact, and rely on the hand-written trade cards turned in by brokers and traders to their clearing firms, OIA occasionally has problems identifying the exact time at which a given transaction took place. Indeed, our sample appears to have significant problems with its time-stamps. While the probability that a trade should occur on any particular second is about 1/60 or 1.667, we found that 5.8% of the trades were recorded on the minute and 7.6% were recorded at one second past the minute. Furthermore, while the probability that any trade should occur on a particular minute is also about 1/60, we found that about 3% of trades were recorded on the hour or at 15, 30, or 45 minutes past the hour. This indicates that OIA is often forced to guess the trade time and reports an approximate figure, rounded to the nearest minute or to the beginning of the nearest 15-minute trading session. Outside of these times, volume levels were relatively uniform across seconds and across minutes.

To accommodate the trade spikes that occurred on the minute and at one second past the minute, we aggregate all trades to the minute level, summing variables from 31 seconds past one minute to 30 seconds past the next minute.[9] For the 15-minute volume spikes, we record volume observations that fall on the 15-minute intervals as missing from our dataset. However, dropping these observations eliminates a large portion of our sample, since our regressions typically include at least 6 minutes of lagged volume. To avoid losing too many data points, we substitute a corrected volume level for lagged volume levels which

[9] This leaves open the possibility that some of the traders which incorrectly recorded their time on the minute truncated rather than rounded their trade times. To protect against this bias, we checked our results by lagging the explanatory variables an additional 30-seconds. Lagging the explanatory variables an additional 30 seconds had little impact on the results.

fall on the hour and at 15, 30, and 45 minutes past the hour. Whenever the independent volume variable occurrs at these times we continue to record the observation as missing. To construct the corrected volume during a particular minute, we predict the fraction of volume erroneously reported during that minute, and then subtract this off the total volume, so that what remains should be a measure of trades that actually occurred at that time.[10]

All of the results that follow are robust to the omission of all trade spikes from the dataset, using no reconstructed lagged volumes and aggregating only the 58 seconds during which trading volumes are evenly distributed.

3.3 Ambient Noise Properties

Our measure of the overall sound level is the sum of the log (base 10) of each frequency's level. This measure is employed as it represents the standard metric of sound level used in the sound engineering field. While we did not calibrate our recording device to measure absolute decibels, our sound level measure can be thought of as relative decibels. Since our sound level measure is a based on a logarithmic scale, an increase in our sound level measure of 0.3 indicates approximately a doubling of the sound level. An increase of 0.6 indicates a quadrupling of sound level.

Not surprisingly, the sound level exhibits highly seasonal intra-day patterns. As we can see in Figure 1, a second-by-second plot of the average sound level exhibits a u-shaped intra-day pattern, with a level much higher at the open and close than during the middle of the day. After the opening, the sound level slowly drops over the next hour, stabilizing at some time after 8:00. At the close, the sound level jumps discretely following the one-

[10]Our predicted erroneous volume is constructed as follows. First, we regress the volume that occurred at 15 minutes past the hour for all hours and all days on two lagged and two leading minute volume terms. We then calculate the average of a moving average of three lagged volume numbers for each minute of the day and the average volume per minute of each day, approximating expected volume at each minute of each day by multiplying the moving average term divided by its long-term mean by the average daily volume for each day. Finally, we use the difference between the predicted excess volume from the regressions and the expected volume from the minute/day average calculations as a correction factor.

minute warning bell, and remains at the high level until the 2:00 close. Also, the sound level appears to jump at 7:30, 9:00, and 10:00, which correspond to times at which treasury news announcements take place. To adjust for this seasonality, we calculate the mean daily sound level for each second of our sample. We then subtract a five-second moving average of this mean level from each sound observation. Table 1 displays summary statistics of our deseasonalized sound level measure. Deseasonalizing the data leaves the sound level with an average of -0.003 and a standard deviation of 0.954. The deseasonalized sound level is positively skewed, with a median of -0.138, a minimum of -3.0 and a maximum of 5.4.

3.4 Properties of Prices and Trading Volume

Table 1 displays summary statistics of the price and trade data during our sample period. First, note that there are 63801 price changes during our sample – prices change during 5.9% of our second-by-second observations. Also, price changes are highly clustered. The mean interval between price changes is 28.4 seconds, but 50% occur within eight seconds of each other. Trade data are also highly skewed. Average trade size is 17.9 contracts, but 75% of the trades are for less than 15 contracts. Locals account for 70% of the total number of trades and 57% of the total volume. Brokers trading for customers account for 20% of the trades and for 28% of the total trading volume.[11]

Figures 2 and 3 plot the average number of price changes and contracts traded per minute. The price changes plot appears qualitatively similar to the sound level plot. Price changes exhibit the u-shaped pattern and jump at 7:30, 9:00, and 10:00. There also appears to be a slight jump at 8:00, which was not apparent in the sound data. The volume graph also displays the u-shaped pattern. Here, with spikes at regular 15-minute intervals, we see the inaccuracy of the transaction time-stamps. Taking this distortion into account, the jumps at 9:00 and 10:00 do not appear as substantial as those in the price and sound level data.

[11]The remainder are trades by clearing firms or by traders on behalf of other traders (i.e. options traders hedging into the futures pit).

4 Results: Second-by-Second Frequency

4.1 Price Changes

Our second-by-second regressions determine the ability of the sound level to explain future price change likelihoods over short horizons. To determine whether the sound level forecasts price changes, we create a price change indicator variable which is 1 if the price changed during a given second and zero otherwise.[12] This variable is modeled with lagged price change indicators, lagged sound levels, lagged absolute changes in the Dow futures contract, and dummy variables that control for the time of day.[13]

4.1.1 Linear Probability

The linear probability model regresses the price change indicator directly on explanatory variables, including variables indicating the number of price changes from one second to six minutes ago, the absolute change in the price of the CBOT's Dow contract, the time of day, and the sound level. We report only the estimated coefficients for the sound variables in Table 2. The lagged price change variables are highly significant, as price changes tend to be highly clustered. The time-of-day dummies are important as well, as their coefficients capture the u-shaped intra-day pattern in trading activity. Concurrent changes in the price of the Dow contract are significant, but lagged changes in the Dow's price are not significant.

To be conservative, we begin measuring the sound level three seconds after we believe that sound is observable. The regression includes a series of variables that measure changes in the sound level, including 6 sets of changes over ten seconds and four changes over thirty seconds. The variables also include the deseasonalized sound level about three minutes (183 seconds) before the second of observation. All of the sound level variables are very

[12] An indicator variable of 1 almost always indicates a price change of 1 tick. In 5.9% of the seconds, the price changes by 1 tick. In 0.013% of the seconds, the price changes by more than 1 tick.

[13] We include dummy variables to account for each hour of the day, as well as a dummy variable to account for the opening and closing periods, 1:45-2:00 and 7:20-7:45.

statistically significant, with t-statistics ranging from 24.75 to 35.58. The coefficients also exhibit high economic significance. Changes in the sound level have a standard deviation of one, so a one-standard deviation increase in sound level lagged 43 seconds results in a 1.59% increase in the probability of a price change. Since the unconditional probability of a price change is 5.9%, this implies that a price change is 27% more likely if the sound level has increased by a standard deviation 43 seconds ago. These results are not driven by the linear specification that we report. Results from an unreported probit specification are essentially the same. Our results are also robust to leaving out the 3-minute lagged sound level.

4.1.2 Hazard Model

One shortcoming of the second-by-second linear probability model is that it treats all observations as equally important. Since price changes only occur 5.9% of the time and there are typically long stretches of time over which no price changes occur, an important alternative approach is to focus only on periods surrounding a price change. A hazard model represents one such approach. Instead of forecasting price changes during the next period of time, a hazard model focuses on explaining the interval of time that can be expected between adjacent price changes. This means that the hazard model uses sound and other information only immediately prior to a given price change to forecast how long before the price changes again. The predicted interval has the economic interpretation of the expected minimum holding period once a trade is placed.

Table 3 reports our hazard model results. As can be seen, the results are consistent with those of the linear probability model. When the sound level increases, price changes occur more frequently and the expected interval shortens. Because the hazard model relies only on sound data which immediately precedes periods of trading activity, the statistical and economic significance of the results is at least as high as in the linear probability case. Our model is an accelerated failure time model that assumes a gamma distribution for the intervals between price changes. Holding all else equal, a one standard deviation increase in sound level lagged 43 seconds leads to an 22% decline in the expected holding period (from 28 to 22 seconds).

5 Results: Minute-by-Minute Frequency

Because the timing of some trades were not accurately recorded to the second, the minute frequency is the highest which our volume data allow. Also, since our second-by-second results demonstrate that the sound level lagged by up to three minutes is important in predicting price changes, the informativeness of sound at the minute frequency merits investigation. Our sound level variables for these regressions are constructed with the sum of the deseasonalized sound level numbers over each minute.

5.1 Price Changes

For our minute-by-minute frequency study of prices, we model the total number of price changes that occurred during the minute. Hence, our regressions attempt to capture the ability of sound to account for how often the price is expected to change over the next 60 seconds. The results are recorded in Table 4.

Once again, our regression conditions on past price changes, past changes in the Dow contract price, and the time of day. Unlike the previously reported regressions, our minute frequency results also condition on past values of trading volume, going back six minutes. Even after adding past volume, the sound level results are consistent with the second-by-second regressions. Past sound levels are quite economically and statistically important in explaining price changes up to four minutes out. For example, if the minute sound level increases by one-standard deviation (27.5) two minutes lagged the expected number of price changes over the next minute increases by 0.255, for a 7.25% increase in the average number of changes. Although, as one would expect, the coefficients lose magnitude and significance as the lag increases, the four-minute lagged level is still highly significant.

The linear probability, hazard model, and minute-by-minute price change results all lend strong economic and statistical support to Hypothesis 1.

5.2 Trading Volume

Our trading volume figures are the total number of contracts exchanged during the minute interval. We model volume with six minutes of past price changes, nine minutes of past volume, concurrent and lagged changes in the Dow contract price, dummy variables indicating whether or not any blocks have been traded in the past three minutes,[14] dummy variables controlling for the time of day, and the sound level. Estimated coefficients on the sound level variables in the regression of total volume are reported in Table 5.

Again, the sound level coefficients are highly economically and statistically significant up to four minutes back. A one-standard deviation (27.5) increase in the sound level two minutes lagged generates an increase of 147 in the expected number of contracts traded over the next minute. This represents a 16% increase from the average number of contracts traded per minute. As with the price change results, while the coefficients decrease in value and magnitude with higher lags, they remain significant up to four minutes out.

These results offer clear support for Hypothesis 2. They are striking because they identify a way in which the sound level is not simply replicating information contained in a limit order book. Since the sound level helps forecast future total volume levels, it is likely to contain information which forecasts the arrival of new market orders in the future. As a result, the information contained in the sound level is likely to not be easily replicated in electronic exchanges that display a limit order book.

5.3 Market Breadth

An important dimension of trading activity is how widespread trading is among participants at a given point in time. If the sound level can forecast the relative number of trading opportunities that one can expect to face in the future, then it may be information that

[14]For our purposes, a block is defined as a trade of 775 or more contracts by a single trader in a one minute interval. See section 5.4 for more detail.

is useful to trading decisions. However, constructing a measure of market breadth that is independent of other measures of trading activity is not a trivial task. The relative number of traders participating at a given point in time is hard to explain because it is highly correlated with the quantity traded. There simply is not enough independent information in the number of participating traders to explain. We tried a variety of specifications, including accounting for the number of traders conditional on current volume, but had no success. Hence, we are unable to find clear support for Hypothesis 3. However, in explaining a more extreme measure of breadth, whether a block trade occurs, the sound level is important.

5.4 Block Trades

An alternative measure of breadth is whether a single trader trades an unusually large quantity of contracts over a short period of time. If a single broker needs to execute a market order of 1000 contracts,[15] his impact on price and the information he conveys to other market participants may be quite distinct from periods of more dispersed trading activity. To identify minutes during which block trades were executed, we total the number of contracts traded by each participant during each minute and identify the largest number of trades a single trader accounted for each minute. We then define the "block size" as 775 contracts – so that during only (approximately) 5% of the minutes did a single trader account for more than this volume – and assign a value of one to the block trade indicator variable for the minutes during which a block trade occurred. Of course, this definition leaves the possibility that several block trades may have taken place during some minutes. While only 36.9% of our block trading minutes had multiple blocks executed, and 95% had three or less, our indicator variable should be interpreted as an indicator of minutes during which at least one block trade occurred. Brokers executed the majority, 55.8%, of the block trades.

As before, we model block trades with past price changes, past volume, concurrent and

[15] A one-tick difference in execution costs his client $31,250.

past Dow price changes, time of day dummies, past block trades, and the sound level. The results are reported in Table 6. The table confirms that increases in the sound level result in a greater likelihood of a block trade. The coefficients are statistically significant up to four minutes out. To demonstrate the model's economic significance, a one-standard deviation increase in sound level lagged two minutes increases the probability of at least one block trade occurring over the next minute by 1.6%. Since block trades actually occur in 4.6% of the minutes, this represents a 35% increase in block likelihood. This finding is supportive of Hypothesis 4.

5.5 Trader Type

Finally, the sound level may convey information about the type of trader participants can expect to face in subsequent activity. Our measure of average trader type during a given minute is the percentage of contracts traded by brokers fulfilling customer orders during a given minute.[16] To see whether the sound level conveys information about the participants' expectations of trade composition, we regress the sound level on average trader type. We also include lagged values of trader type, lagged price changes, lagged volume, lagged block trade indicators, concurrent and lagged changes in the Dow contract price, and dummy variables to account for the time of day in our regression. Since the percentage of volume accounted for by brokers does not have a constant variance throughout the day, we employ weighted least squares in our regression, with an observation's variance assumed proportional to the inverse of total volume. The results of our regression are reported in Table 7.

As is evident from Table 7, sound level increases do not have a consistent effect on average trader type. An increase in sound appears to initially precede an increase in the fraction of customer-generated trades. However, after 3 minutes, a higher sound level presides over a shift in composition in favor of local trading. A one-standard deviation

[16]Or, as local traders term it, the fraction of "paper" coming into the market at a particular point in time.

increase in sound level results in a 0.0031 increase in the portion of customer-generated volume (1.1%), but later results in a 0.0103 decrease (3.7%). The finding that changes in the sound level forecast shifts in the composition of trading volume lends support for Hypothesis 5.

These results can be understood if we recognize that the local traders are essentially market makers who are compensated for providing liquidity. If a higher sound level forecasts a short-term increase in customer-driven trading, it will also likely precede a build-up in local long or short positions. When the filling of customer orders has subsided, trading will then shift to more activity by locals as they unwind their positions. For this reason, coefficients on lagged sound levels can be expected to change in sign from positive to negative. Consistent this conjecture, the coefficients on lagged trader type (not reported) are positive for the first three minutes but negative for lags four through six.

6 Robustness Checks

While the results presented above are quite strong, the variety of data problems confronted in Section 3, ranging from synchronizing timestamps, to deseasonalizing sound levels, to adjusting for abnormalities in volume levels, justify remaining skepticism. To address these concerns, we examine a wide variety of alternative specifications to check for robustness.

The first possibility is that our results are driven by sound level increases that simply announce the arrival of publicly observable news. For example, if everyone knows an important announcement by the Federal Reserve will take place shortly, and the sound level increases as traders prepare to take positions, it would be unsurprising to find that this precedes periods of increased volume and volatility. To allow for this possibility, we ran our tests on a sample that excluded two minutes before and five minutes after all 148 scheduled news announcements listed by CBOT on their financial calendar during the two-month study.[17] This led to no discernable effect, as all results remained virtually

[17]The CBOT's financial calendar is available on the World Wide Web at

unchanged.

A second possibility is that timing problems still pervade our data. Although we are highly confident that we have fitted our sound timestamps to within a second of those of the time and sales data, it is still conceivable that inaccuracies remain. For example, there may be more of a delay between the time a trade takes place and the time the price is actually recorded than the CBOT recognizes. Additionally, as mentioned earlier, it is possible that the volume spikes that occur on the minute and one second after the minute are not a result of rounding of some transaction timestamps but are due to truncation. To accommodate these possibilities, we ran our tests after lagging the sound level an additional 30-seconds. Again, no substantial changes in the results could be detected.

We conducted a number of additional checks. We ran our tests on the pre- and post-July subsamples. Although the coefficients were slightly higher during the second period, they were still significant and qualitatively similar across the two subsamples. To ensure the results were not driven by peculiarities surrounding the open and close, we ran the tests on a sample that excluded observations before 7:45 a.m. and after 1:45 p.m. The resulting coefficients were largely unchanged and remained highly significant. We examined our second-by-second regression for serial correlation of the error terms and found no autocorrelation.

For all of our results, we tried a number of different variations in the test specification, including altering the lag structures, changing frequencies, and including and omitting different explanatory variables. We choose to report the particular results in Tables 2 through 7 because they are relatively easy to interpret, but the results of each test that we ran were the same as those we report. In fact, we could not come up with a reasonable specification which would make our findings disappear. As a result, we are fairly confident that the conclusions we are drawing from the data are not an artifact of the sample period, the specification, or a failure to control for important omitted factors.

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http://www.cbot.com/mplex/reports/calfi.htm.

7 Conclusion

This paper has studied an unusual time-series, the ambient noise level of a trading pit, to help improve our understanding of an important issue in financial economics – how markets process information in reaching equilibrium. The claim of this paper is that market participants are not relying solely on easily-observable data, such as past prices, trading volumes, or news announcements, in determining their supply and demand schedules. The evidence presented herein suggests that the communication and processing of highly subtle and complex non-market signals by traders plays a central role in determining equilibrium supply and demand conditions.

A key implication of this research is that in the trading arena, machine may not be an appropriate substitute for man. Current electronic trading mechanisms are clearly not equipped to convey the kinds of signals for which a sound level is likely to proxy. Certainly computer terminals can be equipped to offer some conveyance of non-market signals. But their ability to replicate the variety of signals that can be communicated in a face-to-face setting, for example, fear in a trader's voice, is likely to be limited. As a result, if trading volumes migrate to electronic exchanges, much of this information will be lost. The welfare implications of losing this information merit further study.

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Table 1: Summary Statistics

Table 1 presents summary statistics for the variables used throughout the paper. There are 1075447 complete observations of the variables measured every second and there are 15060 complete observations measured every minute.

Panel A: Variables Measured Every Second

Variable	Mean	Std Dev	Min	Max
Deseasonalized Sound Level	-0.003	0.954	-3.0	5.4
Price Change Dummy	0.059	0.235	0.0	1.0
Interval between Changes	28.36	39.56	1.0	605.0
Absolute Change in DJIA	0.24	1.05	0.0	393.0

Panel B: Variables Measured Every Minute

Variable	Mean	Std Dev	Min	Max
Sum of Deseasonalized Sound	-0.19	38.04	-114.7	172.9
Number of Price Changes	3.52	2.84	0.0	20.0
Trading Volume (Contracts)	927.34	1045.72	0.0	14156.0
Number of Traders Trading	70.39	58.20	0.0	424.0
Indicator of a Block Trade	0.046	0.21	0.0	1.0
Customers' Fraction of Trade	0.278	0.13	0.0	1.0
Sum of Abs. Changes in DJIA	14.13	14.73	0.0	821.0

Table 2: Price Change Regression with Second-by-Second Data

Table 2 presents the results of a linear probability model regression in which the dependent variable is one in seconds when the 30-year bond futures price changed. The regression contains independent variables representing the number of price changes going back six minutes, the concurrent and lagged (up to three seconds) amount of change in the Dow futures contract, the time of day, and the ambient noise level. Only sound level parameter estimates are reported, where L_t is the sound level t seconds before the period of observation. The regression's adjusted R^2 is 0.019, it is estimated with 1075447 observations, and its F-statistic is 468, with a corresponding P-value of 0.0001.

Variable	Coefficient	Std Error	T-Stat	P-Value
$L_3 - L_{13}$	0.0070	0.000284	24.75	0.0001
$L_{13} - L_{23}$	0.0122	0.000358	34.05	0.0001
$L_{23} - L_{33}$	0.0144	0.000405	35.58	0.0001
$L_{33} - L_{43}$	0.0155	0.000439	35.30	0.0001
$L_{43} - L_{53}$	0.0159	0.000465	34.28	0.0001
$L_{53} - L_{63}$	0.0160	0.000483	33.09	0.0001
$L_{63} - L_{93}$	0.0164	0.000483	33.85	0.0001
$L_{93} - L_{123}$	0.0165	0.000500	32.96	0.0001
$L_{123} - L_{153}$	0.0164	0.000513	31.94	0.0001
$L_{153} - L_{183}$	0.0162	0.000518	31.20	0.0001
L_{183}	0.0156	0.000512	30.51	0.0001

Table 3: Price Change Hazard Model

Table 3 presents the results of estimating a hazard model in which the dependent variable is the number of seconds between changes in the price of the 30-year bond futures contract. The model is an accelerated failure time model based on a gamma distribution for the intervals between price changes. It incorporates independent variables representing the number of price changes going back six minutes, the concurrent and lagged (up to three seconds) amount of change in the Dow futures contract, the time of day, and the ambient noise level. Only sound level parameter estimates are reported, where L_t is the sound level t seconds before the period of observation.

Variable	Coefficient	Std Error	χ^2 Stat	P-Value
$L_3 - L_{13}$	-0.136	0.00548	611.90	0.0001
$L_{13} - L_{23}$	-0.208	0.00681	928.31	0.0001
$L_{23} - L_{33}$	-0.230	0.00774	878.69	0.0001
$L_{33} - L_{43}$	-0.243	0.00841	834.02	0.0001
$L_{43} - L_{53}$	-0.246	0.00895	758.86	0.0001
$L_{53} - L_{63}$	-0.246	0.00929	703.05	0.0001
$L_{63} - L_{93}$	-0.248	0.00926	714.50	0.0001
$L_{93} - L_{123}$	-0.249	0.00955	679.26	0.0001
$L_{123} - L_{153}$	-0.249	0.00980	645.76	0.0001
$L_{153} - L_{183}$	-0.252	0.00989	648.99	0.0001
L_{183}	-0.238	0.00975	596.88	0.0001

Table 4: Price Changes per Minute Regression

Table 4 presents the results of estimating a linear regression model in which the dependent variable is the number of price changes occuring in one minute. The model incorporates independent variables representing the number of price changes going back nine minutes, volume going back six minutes, the concurrent and lagged (up to three minutes) amount of change in the Dow futures contract, the time of day, and the ambient noise level. Only sound level parameter estimates are reported, where L_t is the sound level t minutes before the period of observation. The regression's adjusted R^2 is 0.38, its F-statistic is 294 (with a P-value of 0.0001), and the number of observations is 15060.

Variable	Coefficient	Std Error	T-Stat	P-Value
$L_1 - L_2$	0.01032	0.00087	11.91	0.0001
$L_2 - L_3$	0.00928	0.00102	9.09	0.0001
$L_3 - L_4$	0.00772	0.00109	7.10	0.0001
L_4	0.00717	0.00098	7.32	0.0001

Table 5: Volume per Minute Regression

Table 5 presents the results of estimating a linear regression model in which the dependent variable is the number of contracts traded in one minute. The model incorporates independent variables representing the number of price changes going back six minutes, volume going back nine minutes, the concurrent and lagged (up to three minutes) amount of change in the Dow futures contract, whether or not a block has been traded in each of the last three minutes, the time of day, and the ambient noise level. Only sound level parameter estimates are reported, where L_t is the sound level t minutes before the period of observation. The regression's adjusted R^2 is 0.46, its F-statistic is 374 (with a P-value of 0.0001), and the number of observations is 15060.

Variable	Coefficient	Std Error	T-Stat	P-Value
$L_1 - L_2$	5.36	0.298	17.99	0.0001
$L_2 - L_3$	5.24	0.351	14.93	0.0001
$L_3 - L_4$	4.74	0.374	12.67	0.0001
L_4	3.62	0.337	10.74	0.0001

Table 6: Block Trade Regression

Table 6 presents the results of estimating a linear probability model in which the dependent variable is one in each minute during which at least one trader buys or sells a block, or 775 or more contracts. The model incorporates independent variables representing the number of price changes going back six minutes, volume going back six minutes, the concurrent and lagged (up to three minutes) amount of change in the Dow futures contract, whether or not a block has been traded in each of the last three minutes, the time of day, and the ambient noise level. Only sound level parameter estimates are reported, where L_t is the sound level t minutes before the period of observation. The regression's adjusted R^2 is 0.055, its F-statistic is 29.2 (with a P-value of 0.0001), and the number of observations is 15063.

Variable	Coefficient	Std Error	T-Stat	P-Value
$L_1 - L_2$	0.000556	0.0000788	7.05	0.0001
$L_2 - L_3$	0.000577	0.0000928	6.22	0.0001
$L_3 - L_4$	0.000362	0.0000989	3.66	0.0003
L_4	0.000267	0.0000889	2.99	0.0027

Table 7: Customer Orders Versus Local Trading Regression

Table 7 presents the results of estimating a linear regression in which the dependent variable is the fraction of all contracts traded due to customer orders. The model incorporates independent variables representing the fraction of trade due to customer orders during the last six minutes, the number of price changes going back six minutes, volume going back six minutes, the concurrent and lagged (up to three minutes) amount of change in the Dow futures contract, whether or not a block has been traded in each of the last three minutes, the time of day, and the ambient noise level. Only sound level parameter estimates are reported, where L_t is the sound level t minutes before the period of observation. Because we expect the residuals of this regression to exhibit heteroskedasticity, we estimate the regression with weighted least squares, where the weights are the quantity traded plus 0.001. The regression's adjusted R^2 is 0.04, its F-statistic is 16.71 (with a P-value of 0.0001) and it is estimated with 13979 observations.

Variable	Coefficient	Std Error	T-Stat	P-Value
$L_1 - L_2$	0.000081	0.000041	1.97	0.0491
$L_2 - L_3$	-0.000024	0.000048	-0.50	0.6151
$L_3 - L_4$	-0.000102	0.000052	-1.97	0.0484
L_4	-0.000243	0.000047	-5.15	0.0001

Figure 1: Daily Pattern in the Sound Level

Figure 1 plots the pattern of the sound level over the typical trading day. The sound level plotted is the average of the sound level taken each second across the 46 days of the sample.

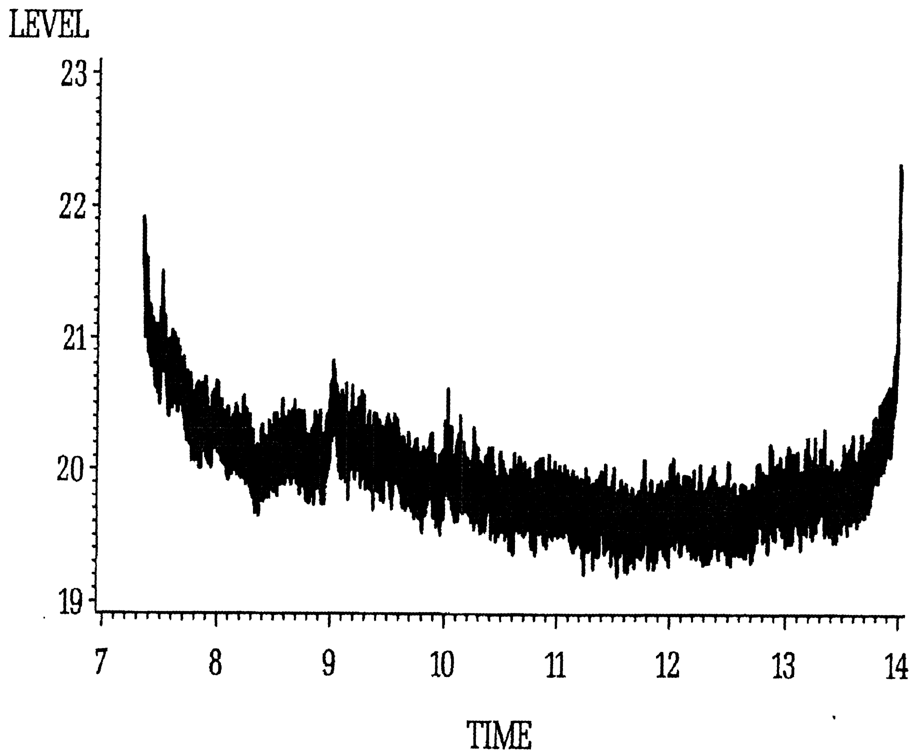

Figure 2: Daily Pattern in Price Changes per Minute

Figure 2 plots the pattern of price changes per minute over the typical trading day. The number of price changes plotted is the average price changes per minute taken each minute across the 46 days of the sample.

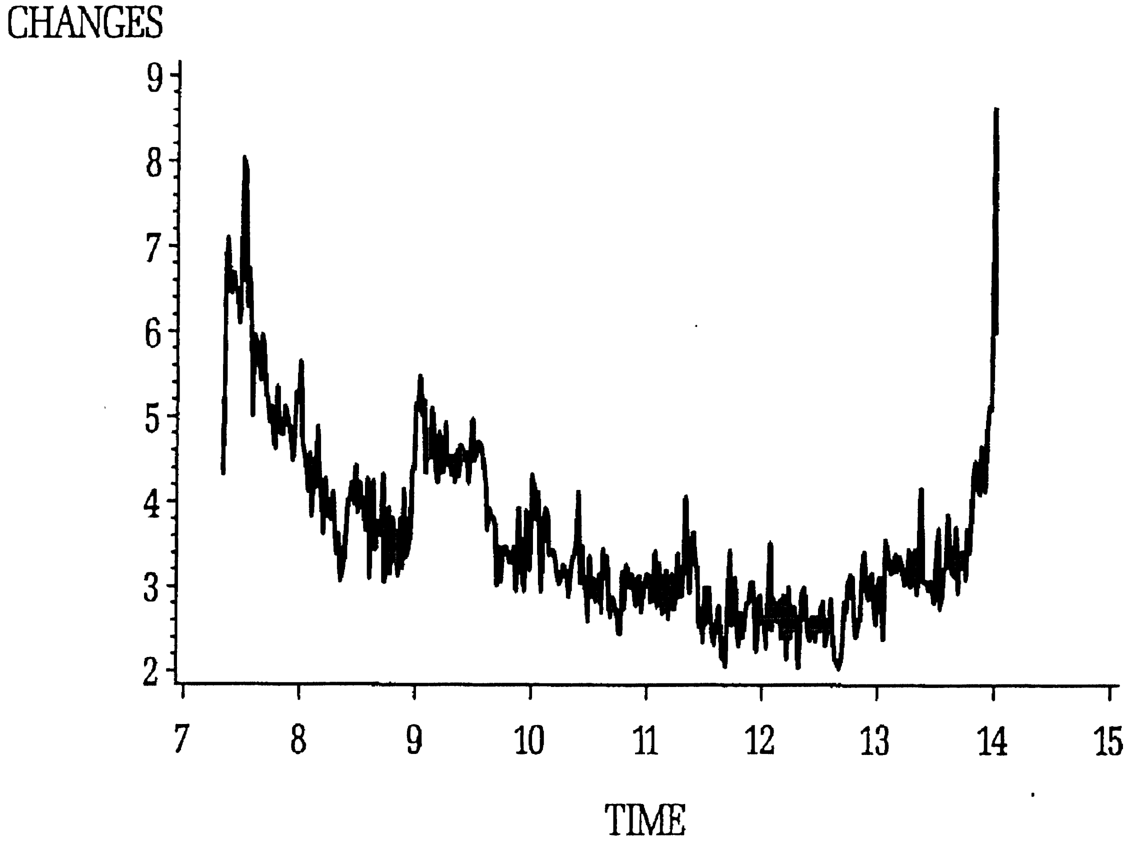

Figure 3: Daily Pattern in Volume per Minute

Figure 3 plots the pattern of trading volume per minute over the typical trading day. The volume plotted is the average volume per minute taken each minute across the 46 days of the sample.